SETAC-Europe LCA Working Group 'Data Availability and Data Quality'

Preamble. Data collection for life cycle inventories (LCI) is still a critical factor for successful work in the area of Life Cycle Assessment (LCA). To facilitate reliable LCI data collection, the SETAC-Europe LCA Working Group 'Data Availability and Data Quality' was formed in April 1998. The goal of the Working Group is to focus on the key features of improving the efficiency and quality of data collection (Fig. 1).

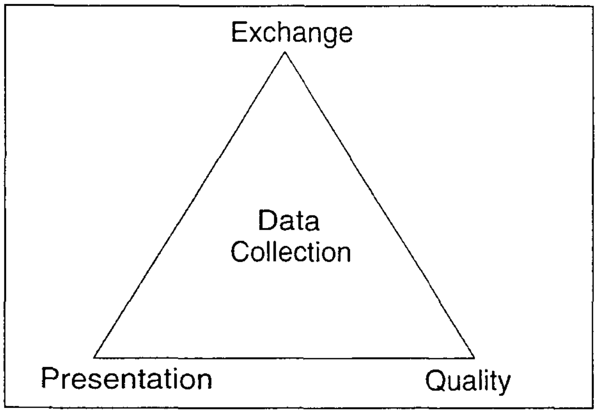

Fig. 1: The key features of data collection

A series of five articles presenting the activities of the working group and its five subgroups through the past three years is being published in Int J LCA. This issue provides the first three subgroup papers: A description of how to assess data quality is presented in the article 'Framework for Modelling Data Uncertainty in Life Cycle Inventories' (Huijbregts et al. 2001). The second article focuses on the driving forces for data exchange (Van Hoof et al. 2001). The third article deals with the availability and quality of energy, transport and waste models (Braam et al. 2001).

Two forthcoming papers concern recommendations for a standardized list of environmental interventions (Hischier et al. 2001) and interfaces to existing software (Jean et al., in preparation).

On the occasion of the 11th Annual Meeting of SETAC-Europe in Madrid, Spain, 6-10 May 2001, the working group has met for its last session to conclude its work. The full report of the SETAC Working Group 'Data Availability and Data Quality' will be published after external peer review as a 'Code of Life Cycle Inventory Practice' by SETAC (De Beaufort & Bretz 2001). The results are fed into the ISO 14048 finalisation process and lay a foundation for the newly starting LCI subprogram of the UNEP-LCI Life Cycle Initiative. Thus, Madrid has become an important step for the future advancement of LCI data availability and data quality.

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Jean P et al., Interfaces to existing software, in preparation

Framework for Modelling Data Uncertainty in Life Cycle Inventories

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Abstract. Modelling data uncertainty is not common practice in life cycle inventories (LCI), although different techniques are available for estimating and expressing uncertainties, and for propagating the uncertainties to the final model results. To clarify and stimulate the use of data uncertainty assessments in common LCI practice, the SETAC working group 'Data Availability and Quality' presents a framework for data uncertainty assessment in LCI. Data uncertainty is divided in two categories: (1) lack of data, further specified as complete lack of data (data gaps) and a lack of representative data, and (2) data inaccuracy. Filling data gaps can be done by input-output modelling, using information for similar products or the main ingredients of a product, and applying the law of mass conservation. Lack of temporal, geographical and further technological correlation between the data used and needed may be accounted for by applying uncertainty factors to the non-representative data. Stochastic modelling, which can be performed by Monte Carlo simulation, is a promising technique to deal with data inaccuracy in LCIs.

Keywords: Data gaps; data inaccuracy; data uncertainty; unrepresentative data; general framework; life cycle inventory (LCI); Monte Carlo simulation; sensitivity analysis; SETAC LCA-WG, Data Availability and Data Quality; uncertainty assessment; uncertainty importance

Introduction

A major problem affecting the application of LCA-based tools concerns the data about resource use and emissions that are used in life cycle inventories (Fava et al. 1994, Weidema and Wesnæs 1996). Actual monitoring of resource use and emissions is not common practice, many producers do not provide data necessary for LCAs, and if data are available for the public, these tend to be dated and may not reflect current technologies. It is important to know to what extent the outcome of an LCA is affected by data uncertainty in the inventory, as it may be helpful for decision makers in judging the significance of the differences in product comparisons, options for product improvements or the assignment of ecolabels.

Here, data uncertainty is divided into lack of data, and data inaccuracy. In addition, lack of data is further specified as a complete lack of data (data gaps) and a lack of representative data for the product system(s) under study (**Fig. 1**). How to handle the uncertainty related to these types of data uncertainty is described below.

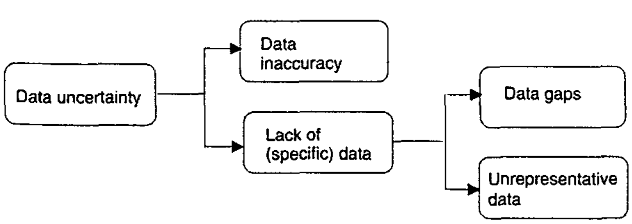

Fig. 1: Division of different types of data uncertainty

1 Lack of Data

1.1 Data gaps

There may be gaps in data concerning (i) flows between economic processes and (ii) interventions with the environment. Generally, missing information in LCIs is implicitly set to *zero*. Errors introduced by such omissions cause a systematic bias towards lower values. Ignorance is thereby rewarded: a comparison between a well-documented process and its less completely analyzed counterpart will be biased towards favoring the latter – a very undesirable result of an LCI. Obviously, the lack of (specified) data on inter-process flows and environmental interventions should be prevented as much as possible. In the (near) future, the recommendations on a standard inventory list including guidelines for reporting sum parameters may prevent the occurence of data gaps to some extent (Hischier et al. 2001). Nevertheless, dealing with data gaps in current data sets will still be necessary. Possibilities to do this are given below.

1.1.1 Inter-process flows

If a process system is modelled for the collection of LCI data, all known process steps of significance should be considered, with their known or estimated amounts entering or leaving the main system. If life cycle inventory data for a production process are impossible to obtain, input-output models, such as the Economic Input Output-Life Cycle Assessment (Carnegie Mellon University 1999, Hendrickson et al. 1998), LCNetBase (Norris 1997) and the Missing Inventory Estimation Tool (Suh 2000), may be used instead. Using the estimated price of missing flows as input, direct and indirect environmental emissions and resources can be calculated with these models. The input-output model approach should be seen as an estimation method for lacking data, as there are important limitations involved related to the use of current input-output models in LCA case studies (Carnegie Mellon University 1999, Suh 2000). One drawback of the available software is that it only covers the United States, while information representative for other regions may be needed in the processes under study. Furthermore, while the input-output models strive to include comprehensive data, some sources are incomplete. For instance, capital goods are not counted as inputs in the input-output convention, toxic emissions are not reported for all industrial sectors, and some impacts such as land use and habitat destruction are not included. Another problem is the level of aggregation. Even with 500 sectors, more detailed information on particular products or processes is in most cases necessary in LCIs.

Inter-process flows for which data are lacking can also be estimated by using information for the most similar 'analogous' process or product for which data are available. Similar flows with respect to chemical, physical or other comparable properties for which process data are known may be used for this purpose. For example, missing data for a pigment additive in LDPE may be estimated by the process "production of inorganic chemicals" in the ETH-database (Frischknecht et al. 1996). Another option in this respect is to replace small quantity additives not with their closest analog, but with the main ingredients of the product. For instance, Boustead (1997) replaces additives in polyurethane products by their main ingredients, TDI, MDI and polyol. Expert judgements about 'what is reasonably similar' or 'what can reasonably be replaced by the main ingredients of the product' will differ from practitioner to practitioner, introducing a degree of arbitrariness to the results of these two approaches.

1.1.2 Environmental interventions

Identifying data gaps in environmental interventions, such as pollutant flows and mineral extractions per unit of process output, may be more complicated than finding data gaps in inter-process flows; on the other hand, if *some* information on the inputs and outputs is available, it can often be inferred that the adequate book-keeping of raw materials and energies and the appropriate analytics of effluents has been performed (Bretz and Frankhouser 1996). An inspection of the parameter lists found in literature sources for LCIs often reveals obvious gaps. As with data on inter-process flows, more complete accounting for environmental interventions may also be obtained from closest analog processes. For example, the inventory for coal-fired steam boilers in Habersatter (1991) shows no heavy metal emissions. The data user can try to fill the gaps with data from other sources (e.g. Habersatter and Fecker 1998). Other sources may also be used to further specify sum parameters, such as 'hydrocarbon emissions', in more detail. For instance, hydrocarbon emissions related to the Polypropylene production (Boustead 1993) may be further specified by more detailed information from Frischknecht et al. (1996).

Furthermore, a comparison between the process *inputs* and stoichiometry (e.g. of heavy metals, CFCs etc. going *into* the process), and the composition of the intermediate good, often reveals gaps in the *output* parameter list. The law of mass conservation frequently helps to fill data gaps here. Known constituents of a product must appear somewhere on the input list, and known inputs that do not remain in the final product must leave the process as waste. A major drawback of mass balance calculations may be the underestimation of relative losses with high environmental impacts. There may also be a failure in identifying the final fate of the wastes or the environmental media to which the emissions are released. Nevertheless, using a mass balance is clearly superior to a total disregard of the mass balance.

1.2 Lack of representative data

Not only complete lack of data, but also lack of *representative* data between the product system under study and the actual data may result in unreliable results. Temporal, geographical and further technological correlation between the data used and data needed should be considered (Table 1, Weidema 1998). According to Weidema (1998), "the indicator 'temporal correlation' expresses the degree of accordance between the year of the study and the year of collection of the obtained data. The indicator 'geographical correlation' expresses the degree of accordance between the production conditions in the area relevant for the study and in the geographical area covered by the data obtained. The indicator 'further technological correlation' concerns all other aspects of correlation than the temporal and geographical considerations." As can be derived from the definitions of the three data quality indicators, they are related to the conditions under which the data are valid, and therefore dependent on the goals of the study in which the data are applied.

It should be stressed that the scores in Table 1 serve as identification numbers only, and should not be interpreted as a certain quantitative representation of data representativeness (Weidema 1998). Although a quantitative assessment of the uncertainty related to the use of unrepresentative data within an LCI study may be preferable, it is also extremely difficult. For instance, imagine quantifying the uncertainty arising from using data for Canadian car manufacturing in 1980, while one needs data for tractor manufacturing in the US for the year 1995.

A procedure to quantitatively deal with unrepresentative data in LCIs, consistent with the notion of systematic bias, may be very valuable. In this respect, it may be useful to include so-called 'uncertainty factors' for non-representative data in LCIs. An uncertainty factor may be introduced for each data quality indicator (Equation 1), where the actual uncertainty factor may depend on the temporal, geographical and technical distances between the modelled process and the data used. Quantitative estimates of these uncertainty factors may be obtained through empirical analysis of time series and cross-sectional data on process inputs and releases per unit of output. Note that the introduction of uncertainty factors in LCIs is analogous to the application of 'assessment factors' in the derivation of environmental quality objectives for ecological risk assessment (EC 1996).

$$E'_{x,k} = UF_{t,k} \times UF_{g,k} \times UF_{ft,k} \times E_{x,k} \qquad (1)$$

in which $E'_{x,k}$ is the corrected emission of substance x per unit process k (kg); $UF_{t,k}$ is the uncertainty factor represent-

Table 1: Pedigree matrix with three data quality indicators (taken from Weidema 1998)

Indicator score	1	2	3	4	5
Temporal correlation	Less than 3 years of difference to year of study	Less than 6 years difference	Less than 10 years difference	Less than 15 years difference	Age of data unknown or more than 15 years of difference
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown area or area with very different production conditions
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials but from same technology	Data on related processes or materials but from different technology

ing the temporal correlation between the data used and needed for unit process *k* (dimensionless); $UF_{g,k}$ is the uncertainty factor representing the geographical correlation between the data used and needed for unit process *k* (dimensionless); $UF_{ft,k}$ is the uncertainty factor representing the further technological correlation between the data used and needed for unit process *k* (dimensionless); and $E_{x,k}$ is the initial emission of substance *x* per unit process *k* (kg).

Finally, it should be noted that Table 1 contains only three of the five data quality indicators identified by Weidema and Wesnæs (1996) and Weidema (1998). The reason is that the other two data quality impact indicators, 'reliability of the source' and 'completeness', are not related to the issue of data representativeness. These two indicators are covered in a more quantitative way in the sections 'Data gaps' and 'Data inaccuracy' in this paper. However, for a quick data quality overview the use of the semi-qualitative indicators 'reliability of the source' and 'completeness' may still be valuable in LCIs. The reader is referred to Weidema and Wesnæs (1996) and Weidema (1998) for a comprehensive overview of the application of these two other indicators in LCI data quality assessments.

2 Data Inaccuracy

Data inaccuracy may be caused by unprecise measurement methods, (expert) estimations and assumptions, measurements from a small number of sites, and inadequate time periods of measurements pertinent to the processes involved (Huijbregts 1998a). Various methods have been proposed to make data inaccuracy operational in LCA outcomes, such as analytical uncertainty propagation methods (Hoffman et al. 1995, Heijungs 1996), calculation with intervals and fuzzy logic (Chevalier and Le Teno 1996, Becalli et al. 1997), and stochastic modelling (Kennedy et al. 1996, Huijbregts 1998b, Maurice et al. 2000). In particular, stochastic modelling, which can be performed by Monte Carlo simulation, seems to be a promising technique for making data inaccuracy in LCIs operational, as Monte Carlo simulation is widely recognised as a valid technique and the level of mathematics required to perform a Monte Carlo simulation is quite basic (Vose 1996). An explanation of the steps involved in assessing LCI data inaccuracy by Monte Carlo simulation is given below. Fig. 3 shows an overview of the proposed procedure.

First of all, to perform Monte Carlo simulation, parameters have to be specified as uncertainty distributions. In practice, however, it will be a very difficult and time-consuming exercise to characterise the uncertainty ranges for the enormous amount of parameters involved in the inventory analysis. Selecting and applying one or more appropriate methods for identifying and assessing the most important input uncertainties is of vital importance in these cases (Burmaster and Anderson 1994). It is recommended to first perform a sensitivity analysis, sometimes called a perturbation analysis, of the deterministic calculations to determine the parameters important for the probabilistic simulations (Burmaster and Anderson 1994, Heijungs

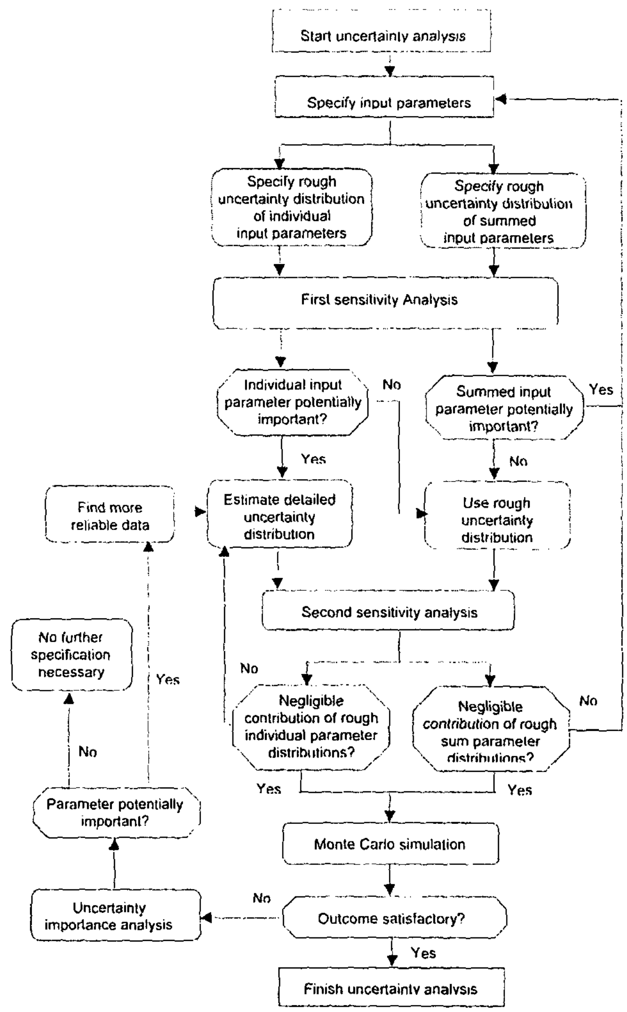

Fig. 3: Scheme for the analysis of data inaccuracy in LCI

1996). Here, the focus may be on the influence of input parameters on outcomes of the inventory, characterisation, normalisation and/or final weightings between impact categories. If the focus is on the outcomes of the inventory, inter-process data, environmental interventions, and data underlying the functional unit should be varied in the sensitivity analysis. Prices of missing flows, used in input-output models, and uncertainty factors, representing temporal, geographical and technical distances between the modelled process and the data used, should also be varied in the sensitivity analysis, if this information is used to prevent the lack of (representative) inventory data. In general only a few input parameters will be important to specify in further detail, because (i) the values of some inputs account for a dominant fraction of the environmental impact and/or (ii) the ranges of some inputs account for a dominant fraction of the range in environmental impact (Heijungs 1996). In this step one may elect to use a single standard sensitivity range for all parameters (e.g ± 10%), although this approach may fail to highlight highly inaccurate input parameters with only modest influence. A rough solution may be found in the use of a number of wide standard sen-

sitivity ranges and distribution functions for different types of environmental interventions and economic processes (Finnveden and Lindfors 1998, Huijbregts 1998b). A complementary strategy to simplify the analysis is to implement sensitivity ranges for accumulated environmental interventions instead of individual parameters in LCA inventories (see Kennedy et al. 1996, Huijbregts 1998b). This simplification may be particularly useful in the analysis of the potential importance of background data in product assessments. For example, ranges for accumulated environmental interventions per 'MJ heat production' or 't·km transport' could be implemented in the sensitivity analysis. Whenever the sensitivity analysis shows that some of these accumulated environmental interventions may contribute substantially to the uncertainty in model outcomes, a reconstruction of parts of the accumulated inventory will be necessary (Huijbregts 1998b).

The next step is specifying the uncertainty distributions of the potentially important parameters in more detail. A rule of thumb could be that the parameters which together cover, for instance, 90% or 95% of the sensitivity range, should get priority in data refinement efforts. As noted before, a quantitative uncertainty analysis is generally complicated by a lack of knowledge about actual uncertainty of data on inputs to and outputs from industrial processes. One substitute for lack of knowledge is the use of expert judgement to estimate uncertainty ranges (Morgan et al. 1985, Morgan and Henrion 1990, Otway and Winterfeldt 1992, Taylor 1993). In addition, a description in databases of uncertainty ranges for environmental interventions per unit process would substantially improve the feasibility of performing a standard uncertainty analysis in LCAs. A first step in this respect is the development of a common database format, in which uncertainty ranges for average life cycle inventory data should be listed (Singhofen et al. 1996, Weidema 1999).

After specifying the uncertainty distributions for the most important input parameters, a second sensitivity analysis should be applied. This second analysis is necessary because defining parameters in more detail generally results in smaller ranges, which may alter their importance (Ragas et al. 1999). Roughly defined input parameters, found important in the second sensitivity analysis, should also be specified in more detail. If all important input parameters are specified in detail, the Monte Carlo simulation can be applied. This method varies all the parameters at random, but the variation is restricted by the given uncertainty distribution for each parameter. The randomly selected values from all the parameter uncertainty distributions are inserted in the output-equation. Repeated calculations produce a distribution of the predicted output values, reflecting the combined parameter uncertainties. A special form of the Monte Carlo technique is Latin Hypercube simulation which firstly segments the uncertainty distribution of a parameter into a number of non-overlapping intervals, each having a equal probability. This helps stabilize the tails of the output as quickly as possible (Burmaster and Anderson 1994). A model run generally consist of 10,000 iterations, which may be considered sufficient to obtain a representative frequency chart of the output variables (Huijbregts 1998b, Ragas et al. 1999).

As LCAs are in most cases concerned with relative differences (between product systems or between improvement options), it is vital to take into account the interdependency between the product systems under consideration. For instance, environmental interventions due to the same background processes, such as electricity production, should be varied simultaniously for all the product systems under study (Huijbregts 1998b).

Probabilistic uncertainty analysis is useful to make the influence of input data uncertainty on the uncertainty of the model outcomes operational. For the reduction of parameter uncertainty, however, more reliable data must be provided by additional literature research, expert judgement or, ideally, measurements. Parameters which cause the largest spread in the model outcome should get priority. The contribution of the separate parameters to the total uncertainty may be estimated through use of statistical regression techniques (Janssen et al. 1990).

Finally, it should be noted that, although the techniques mentioned above may be useful in dealing with aspects of data inaccuracies in LCA, there is some potential for their misuse. One risk is that, because the techniques provide technical-looking results, they may be inappropriately used as a low-cost substitute for actual scientific research (Morgan et al. 1985). Nevertheless, through LCA peer review and other quality control measures, together with accumulating experience and understanding about uncertainty analysis among LCA practitioners, the danger of misusing these techniques can be minimized.

3 Conclusion

Dealing with data uncertainty should be an integral part of every LCA, as it may supply vital information for decision makers in judging the significance of the differences in product comparisons, options for product improvements or the assignment of ecolabels. However, modelling data uncertainty is still not common practice in life cycle inventories (LCI). To enhance the use of data uncertainty assessments in LCI practice, options to deal with lack of data, unrepresentative data and data inaccuracy are discussed. Filling data gaps by input-output modelling, applying uncertainty factors to non-representative data, and using stochastic modelling to deal with data inaccuracy are identified as potentially promising options to deal with the various types of data uncertainty. It should be stressed, however, that without empirical justification of uncertainty factors and uncertainty ranges applied to LCI data, the relevance of the uncertainty analysis will be limited. Further research towards clarifying uncertainty estimates in LCI data would be very valuable in this respect.

Finally, to keep the actual performance of LCA case studies feasible, it is highly recommended to implement in current LCA software the various tools dealing with data uncertainty.

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